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Expert System Analysis of Electromyogram

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Abstract. Electromyogram (EMG) is the record of the electrical excitation of the skeletal muscles which is initiated and regulated by the central and peripheral nervous system. EMGs have non-stationary properties. EMG signals of isometric contraction for two different abnormalities namely ALS (Amyotrophic Lateral Sclerosis) which is coming under Neuropathy and Myopathy. Neuropathy relates to the degeneration of neural impulse whereas myopathy relates to the degeneration of muscle fibers. There are two issues in the classification of EMG signals. In EMG's diseases recognition, the first and the most important step is feature extraction. In this paper, six non-linear features have been used to classify using Support Vector Machine. In this paper, after feature extraction, feature matrix is normalized in order to have features in a same range. Simply, linear SVM classifier was trained by the train-train data and then used for classifying the train-test data. From the experimental results, Lyapunov exponent and Hurst exponent is the best feature with higher accuracy comparing with the other features, whereas features like Capacity Dimension, Correlation Function, Correlation Dimension, Probability Distribution & Correlation Matrix are useful augmenting features.

Keywords: Myopathy, ALS, Lyapunov exponent, Hurst exponent, Support Vector Machine

I. INTRODUCTION

Movement and position of the limbs are controlled by the electrical signals travelling forward and backward between Muscle fibers, Peripheral and Central Nervous System [1], [2]. Conscientious Registration and interpretation of these muscle electrical potential is called as Electromyogram (EMG).

Due to the emanation of Pathological condition in motor system, whether in spinal cord, the motor neuron, the muscle or the neuromuscular junction the characters of electrical potentials generated during the contraction and relaxation of muscles changes [4]. Careful registration and study of electrical signals in muscles thus can be valuable aid in discovering and diagnosis abnormalities not only in muscles but also in the motor system as a whole [3][5].

EMG classification is one of the most difficult pattern recognition problems because there usually exists small but numerous variations in EMG features, which leads to difficulty in analyzing EMG signals. In muscles diseases recognition, there are two main points, namely *feature selection* and *classifier design*. In general, the methods of feature selection can be divided into two types: the measure of classification accuracy and the valuation using statistical criterion. After that the selection of the best features based on the proposed statistical criterion method is investigated.

For this purpose, we evaluate different kinds of features that have been widely used in EMG diseases recognition. The results of this evaluation and the proposed statistic method can be widely used in EMG applications such as control of EMG robots and prostheses or the EMG diagnosis of nerve and muscle diseases[6],[7],[8].

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The section II and III explain about the data selection filters (Butterworth & Notch), and the features extracted. The section IV gives the results and discussion and conclusion of the context.

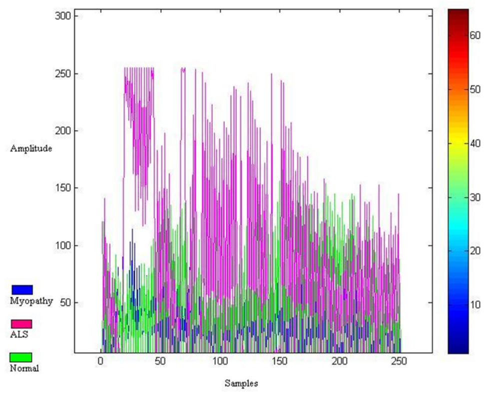

Figure 1. Emg Signal Of Normal, Als, Myopathy Patient From Biceps Brachii Region

II. Data Selection

A. Subjects

For our study, we have chosen 3 groups. First group consisted of 10 normal subjects aged 21-35 years, 4 females and 6 males. All of the 10 subjects are in very good physical condition except one. None in this group had signs or history of neuromuscular disorders. The group with myopathy consisted of 7 patients; 2 females and 5 males aged 19-63 years. The ALS group consisted of 8 subjects; 4 females and 4 males aged 35-67 years. Besides clinical and electrophysiological signs compatible with ALS, 5 of them died within a few years after onset of the disorder, supporting the diagnosis of ALS.

B. Experimental Protocol

The EMG signals were recorded under usual conditions for MUAP analysis. The recordings were made at low (just above threshold) voluntary and constant level of contraction. A standard concentric needle electrode was used. The EMG signals were recorded from bicep brachii of bicep. The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz for 11msec duration with sampling frequency of 10 kHz [8]. Figure 1 shows plot of different types of sample signal where around 250 points of sample signals are taken.

III. Proposed Method

In this paper, we describe each of the following steps involved for the classification of the acquired EMG signal. These steps are: (A) Base line shift for accurate estimation of parameters. (B) Butterworth band pass Filter (C) Notch filter for removing DC power line interference. (D) Various parameters/features calculation.(E) Classifier Design.

A. Base Line Shifting

Generally human being produces static current which will interfere while recording EMG signal. Due to this problem EMG signal shifts upper side from the base line. This defect occurs due to the muscle tension, body movement or some environmental noise.

B. Butterworth Filter

In this paper, we used Butterworth band pass filter which is a combination of low pass filter and high pass filter. Here lower cut off frequency is 5 Hz and higher cut off frequency is 1500 Hz.

C. Notch Filter

Due to the DC power line interference a significant noise appears during EMG acquisition. That should be removed by using Notch Filter at 50 Hz.

D. Feature Extraction & Calculation

In this paper, we are calculating different entropies for classifying above referred EMG signals. Entropies are stated below:

Lyapunov Exponent: It is measure of rate of separation of infinitesimally close trajectories for dynamical system. It gives the rate of exponential divergence from perturbed initial conditions. It is a measure of the rate at which nearby trajectories in phase space diverge. . Thus a value of +1 means separation of nearby orbits doubles on the average in the time interval between data samples represented by Eq. (1).

$$\lambda = \lim_{\substack{t\to\infty \\ |\Delta x_0|\to 0}} \frac{1}{t} ln \frac{|\Delta x(X_0,t)|}{|\Delta x_0|} \qquad (1)$$

The displayed error is estimated from 2.5 times the standard deviation of the slope divided by the square root of the number of trajectories followed. It is given by following [6][12].

Capacity Dimension: It is also known as Hausdorff dimension. It is calculated successively dividing the phase space with embedding dimension D into equal hyper cubes that are occupied with data points with respect to the log of the normalized linear dimension of hypercubes. The capacity dimension of space X is a real number $d_{capacity}$ such that if n($\in$) denotes the minimum number of open sets of diameter less than or equal to $\in$, then n($\in$) is proportional to $\in^{-D}$ as $\in\to 0$. It is represented by Eq. (2).

$$d_{capacity} = -\lim_{\in\to 0+} \frac{\ln N}{\ln\in} \qquad (2)$$

where N is the number of elements forming a finite Space and ϵ is a bound on the diameter of the sets involved (informally, ϵ is the size of each element used to cover the set, which is taken to approach 0) if the limit exists.

Correlation Dimension: It is a method to determine the dimension of space occupied by sets of random points [9], [10]. It provides a good measure of the complexity of the dynamics, i.e. of the number of active degrees of freedom. The correlation dimension is a characteristic of the underlying invariant measure μ. In a certain sense it characterizes how smoothly μ is distributed over the attractor: if μ is a point measure, then α = 0, and if μ is absolutely continuous with respect to Lebesgue measure, then α equals the topological dimension d of X. These are two boundary cases, in general 0<α<d. This paper explains the correlation dimension by Eq. (3).

$$\mathrm{C(r)} = \iint_{\Omega X \Omega}^{\infty} I(\|y_1 - y_2\| \le r)d\mu(y_1)d\mu(y_2) \qquad (3)$$

where I denote an indicator function.

Correlation Matrix: Singular Value decomposition begins with the correlation matrix which is a two dimensional matrix formed by putting the value of the correlation function with tau=0 along the diagonal and putting of the value of the correlation function with tau=1 to the right and left filled [11]. The Eigen values are determined.

Probability Distribution Function: It shows the probability of occurrence of certain data values. We can specify a number of bins between 2 and 128 into which data points are sorted according to their value. The bins all have the same width and are spread uniformly between the lowest and highest data value. It is represented by Eq. (4)

$$\mathrm{F(x)} = \mathrm{F(x)} = \int_{-\infty}^{x} f(t)dt \qquad (4)$$

Hurst Exponent: It is referred to as the "index of dependence," and is the relative tendency of a time series to either strongly regress to the mean or 'cluster' in a direction. The Hurst exponent is used as a measure of the long term memory of time series, i.e. the autocorrelation of the time series as in Eq. (5).

$$E\left[\frac{R(n)}{S(n)}\right] = Cn^H \; as \; n \to \infty \qquad (5)$$

where

$[\frac{R(n)}{S(n)}]$ is the rescaled range.

E[x] is the expected value.

n is the time of the last observation

(e.g. it corresponds to X_n in the input time series).

C is a constant.

E. Support Vector Machine as a classifier

In this paper, after feature extraction, feature matrix is normalized in order to have features in a same range. Simply, SVM classifier was trained by the train-train data and then used for classifying the train-test data.

SVM creates a separating hyper plane between two clusters of data, thus classifying data falling into two different classes. In non-linear classification, same operation was performed by non-linear kernel function, in our case, Gaussian-RBF kernel, given by Eq. (6).

$$k(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / 2\sigma^2) \qquad (6)$$

In this work we take two different group i.e. normal and abnormal (Myopathy & Neuropathy) signal for the classification purpose .We take 70% of signal to train the expert model using SVMStruct a structure with the Kernel Function fields [4],[5]. Kernel function Value is Gaussian Radial Basis Function kernel ('rbf') function handle with a scaling factor, sigma which is varying from 0 values to 10 and takes those which give maximum accuracy.

IV. Result And Discussion

We are classifying EMG signals for differentiating different diseases from the normal. Our classification uses features which has described above. So we are spotting some of the features which produce demarcation between different subjects. Then we train and test the SVM classifier with various extracted features like for EMG. The classifier was also cross validated by taking feature vector in different combinations

From the result we state that Lyapunov Exponent & Hurst Exponent is the best parameter to classify the EMG signals when taken individually and the classification accuracy is around 93%. By taking the combined features Hurst Exponent & Lyapunov Exponent gives us classification accuracy around 88%.

V. Conclusion

In this present study we are analyzing the different class of EMG signals considering some of the best non-linear features. Based on the above features we can state that LLE and Hurst exponent are the best to distinguish the EMG signals. As per the authors the techniques used is a cost effective and time effective approach for analyzing the EMG signals. In future we will compare different machine expertise system for classifying the EMGs for detecting the diseases.

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